CSE 158
Web Mining and Recommender Systems

Introduction
What is CSE 158?

In this course we will build models that help us to understand data in order to gain insights and make predictions.
Examples – Recommender Systems

**Prediction:** what (star-) rating will a person give to a product? e.g. rating(julian, Pitch Black) = ?

**Application:** build a system to recommend products that people are interested in

![Review](https://example.com/review.png)

103 of 115 people found the following review helpful

⭐⭐⭐⭐⭐ Excellent Sci-Fi
Pitch Black was arguably one of the most overlooked films of the early year. Although the setting of the film could seem routine to a casual viewer (space travelers stranded and bickering on a hostile planet infested with alien nasties), director David Twohy's wonderful use of color and stylistic flourish more than makes up for any trivial complaints.

For...

Read the full review >

Published on September 12, 2000 by Eric J. Pray

**Insights:** how are opinions influenced by factors like time, gender, age, and location?
Examples – Social Networks

**Prediction:** whether two users of a social network are likely to be friends

**Application:** “people you may know” and friend recommendation systems

**Insights:** what are the features around which friendships form?
Examples – Advertising

**Prediction:** will I click on an advertisement?

**Application:** recommend relevant (or likely to be clicked on) ads to maximize revenue

**Insights:** what products tend to be purchased together, and what do people purchase at different times of year?
**Examples – Medical Informatics**

**Prediction:** what symptom will a person exhibit on their next visit to the doctor?

**Application:** recommend preventative treatment

**Insights:** how do diseases progress, and how do different people progress through those stages?
What we need to do data mining

1. Are the data associated with meaningful outcomes?
   • Are the data **labeled**?
   • Are the instances (relatively) independent?

   e.g. who likes this movie? **Yes!** “Labeled” with a rating

   e.g. which reviews are sarcastic? **No!** Not possible to objectively identify sarcastic reviews
What we need to do data mining

2. Is there a clear objective to be optimized?
   - How will we **know** if we’ve modeled the data well?
   - Can actions be taken based on our findings?

   e.g. who likes this movie?

   How wrong were our predictions on average?

   \[
   \frac{1}{N} \sum_{u,i}^{N} (r_{u,i} - prediction(u, i))^2
   \]
3. Is there enough data?
   • Are our results statistically significant?
   • Can features be collected?
   • Are the features useful/relevant/predictive?
This course aims to teach

• How to **model** data in order to make **predictions** like those above
• How to **test and validate** those predictions to ensure that they are meaningful
• How to **reason about** the findings of our models

(i.e., “data mining”)

What is CSE 158?
What is CSE 158?

But, with a focus on applications from **recommender systems and the web**

- **Web** datasets

- Predictive tasks concerned with human **activities, behavior, and opinions**
  (i.e., recommender systems)
**Basic** data processing

- Text manipulation: count instances of a word in a string, remove punctuation, etc.
- Graph analysis: represent a graph as an adjacency matrix, edge list, node-adjacency list etc.
- Process formatted data, e.g. JSON, html, CSV files etc.
Expected knowledge

**Basic** mathematics

- Some linear algebra \( Ax = y \rightarrow x = (A^T A)^{-1} A^T y \)
- Some optimization
- Some statistics (standard errors, p-values, normal/binomial distributions)
Expected knowledge

All coding exercises will be done in **Python** with the help of some libraries (numpy, scipy, NLTK etc.)
CSE 158 vs. CSE 150/151

The two most related classes are
• CSE 150 ("Introduction to Artificial Intelligence: Search and Reasoning")
• CSE 151 ("Introduction to Artificial Intelligence: Statistical Approaches")

None of these courses are prerequisites for each other!
• CSE 158 is more “hands-on” – the focus here is on applying techniques from ML to real data and predictive tasks, whereas 150/151 are focused on developing a more rigorous understanding of the underlying mathematical concepts
CSE 258 is the **graduate** version of this class. It is roughly the same, though there are some differences:

- CSE 258 will have more on graphical models (we’ll cover it a little bit in 158, but not much)
- CSE 258 will have a little bit more on optimization (e.g. gradient based methods). We’ll cover these too, but not really with complex derivations – in this class some of the more complex linear algebra / calculus will be treated in more of a “black box” way
- CSE 258 will cover more academic papers

- As long as you do the CSE 158 assessments, you’re welcome to attend either class (but not this week!)
Both classes will be podcast in case you want to check out the more advanced material:

(last year’s links)

CSE158:
http://podcasts.ucsd.edu/podcasts/default.aspx?PodcastId=3746&v=1

CSE258:
http://podcasts.ucsd.edu/podcasts/default.aspx?PodcastId=3747&v=1
In Lectures I try to cover:

- The basic material (obviously)
- **Motivation** for the models
- **Derivations** of the models
  - Code examples
  - Difficult homework problems / exam prep etc.
  - **Anything else you want to discuss**
CSE 158
Web Mining and Recommender Systems

Course outline
The course webpage is available here:
http://cseweb.ucsd.edu/classes/fa17/cse158-a/

This page will include data, code, slides, homework and assignments
(last year’s course webpage is here):
http://cseweb.ucsd.edu/classes/wi17/cse158-a/

This quarter’s content will be (roughly) similar (though the weighting of assignments/midterms etc. is different)
Course outline

This course is in two parts:
1. **Methods** (weeks 1-4):
   - Regression
   - Classification
   - Unsupervised learning and dimensionality reduction
2. **Applications** (weeks 4-):
   - Recommender systems
   - Text mining
   - Social network analysis
   - Mining temporal and sequence data
   - Something else... visualization/crawling/online advertising etc.
Week 1: Regression

• Linear regression and least-squares
  • (a little bit of) feature design
• Overfitting and regularization
  • Gradient descent
• Training, validation, and testing
  • Model selection
How can we use **features** such as product properties and user demographics to make predictions about **real-valued** outcomes (e.g. star ratings)?

How can we prevent our models from **overfitting** by favouring simpler models over more complex ones?

How can we assess our decision to optimize a particular error measure, like the MSE?
Week 2: Classification

• Logistic regression
• Support Vector Machines
• Multiclass and multilabel classification
• How to evaluate classifiers, especially in “non-standard” settings
Week 2: Classification

Next we adapted these ideas to **binary** or **multiclass** outputs

What animal is in this image? Will I **purchase** this product? Will I **click on** this ad?

Combining features using naïve Bayes models

Logistic regression

Support vector machines
Week 3: Dimensionality Reduction

• Dimensionality reduction
• Principal component analysis
  • Matrix factorization
  • K-means
• Graph clustering and community detection
Week 3: Dimensionality Reduction

**Principal component analysis**

**Community detection**
Week 4: Recommender Systems

• Latent factor models and matrix factorization (e.g. to predict star-ratings)
• Collaborative filtering (e.g. predicting and ranking likely purchases)
Week 4: Recommender Systems

Rating distributions and the missing-not-at-random assumption

Latent-factor models
Week 5: Guest lecture?

- Probably about deep learning / automatic optimization etc. (but TBD!)
Week 6: Midterm (Nov 8)!

(More about grading etc. later)
Week 7: Text Mining

• Sentiment analysis
• Bag-of-words representations
  • TF-IDF
• Stopwords, stemming, and (maybe) topic models
Week 7: Text Mining

yeast and minimal red body thick light a Flavor sugar strong quad. grape over is molasses lace the low and caramel fruit Minimal start and toffee. dark plum, dark brown Actually, alcohol Dark oak, nice vanilla, has brown of a with presence. light carbonation. bready from retention. with finish. with and this and plum and head, fruit, low a Excellent raisin aroma Medium tan

Bags-of-Words

What we would like:

87 of 102 people found the following review helpful

Kevin K. (Washington, District of Columbia) - 2015-04-16 04:10:50

I will first say this is a fantastic review of a bad movie. I have to be honest, I found the movie to be very enjoyable, even if it was not the best movie I have ever seen. However, when I got home I was very disappointed in the quality of the movie. The acting was terrible, the special effects were not good, and the plot was not coherent. In fact, I felt that the movie was not worth my time and I did not really enjoy it at all.

The Chronicles of Riddick

(review of "The Chronicles of Riddick")

Document topics

Action: action, loud, fast, explosion...

Sci-fi: space, future, planet...

Sentiment analysis

Topic models
• Power-laws & small-worlds
  • Random graph models
  • Triads and “weak ties”
• Measuring importance and influence of nodes (e.g. pagerank)
Week 8: Social & Information Networks

- Hubs & authorities
- Power laws
- Small-world phenomena
- Strong & weak ties
Week 9: Advertising

Matching problems

AdWords

Bandit algorithms
Week 10: Temporal & Sequence Data

- Sliding windows & autoregression
  - Hidden Markov Models
  - Temporal dynamics in recommender systems
- Temporal dynamics in text & social networks
Week 10: Temporal & Sequence Data

Topics over time

Social networks over time

Memes over time
There is no textbook for this class

- I will give chapter references from *Bishop: Pattern Recognition and Machine Learning*

- I will also give references from Charles Elkan’s notes ([http://cseweb.ucsd.edu/classes/fa17/cse158-a/files/elkan_dm.pdf](http://cseweb.ucsd.edu/classes/fa17/cse158-a/files/elkan_dm.pdf))
Evaluation

- There will be **four** homework assignments worth 8% each. Your **lowest grade** will be dropped, so that 4 homework assignments = 24%
- There will be a midterm in week 6, worth 26%
- One assignment on recommender systems (after week 5), worth 25%
- A short open-ended assignment, worth 25%
Evaluation

HW = 24%
Midterm = 26%
Assignment 1 = 25%
Assignment 2 = 25%

Actual goals:
• Understand the basics and get comfortable working with data and tools (HW)
• Comprehend the foundational material and the motivation behind different techniques (Midterm)
• Build something that actually works (Assignment 1)
• Apply your knowledge creatively (Assignment 2)
Evaluation

• Homework should be delivered by the beginning of the **Monday lecture in the week that it’s due**
• All submissions will be made **electronically** (instructions will be in the homework spec, on the class webpage)
Schedule (subject to change but hopefully not):

Week 1: Hw 1 out
Week 3: Hw 1 due, Hw2 out
Week 5: Hw 2 due, Hw3 out, Assign. 1 out
Week 6: midterm
Week 7: Hw 3 due, Hw4 out, Assign. 2 out
Week 8: Assignment 1 due
Week 9: Hw4 due
Week 10: Assignment 2 due
Previous assignments...
Assignment 1

- Prediction tasks on Amazon clothing data, run as a competition on Kaggle

Rating prediction

Purchase prediction

Helpfulness prediction
Assignment 1

- We’ll do something similar this year, but on Google Local data.
Assignment 2

Raw rating data  binned regression  dual regression

Andrew Prudhomme – “Finding the Optimal Age of Wine”
Assignment 2

ratings vs. time

ratings vs. review length

Ruogu Liu – “Wine Recommendation for CellarTracker”
Assignment 2

positive words in wine reviews

negative words in wine reviews

cellartracker:

positive words in beer reviews

negative words in wine reviews

RateBeer:

Ben Braun & Robert Timpe – “Text-based rating predictions from been and wine reviews”
User age

- Rating vs. age
- Aroma vs. age
- Day of week vs. age
- Year vs. age
- Hour of day vs. age
- Category vs. age
Diego Cedillo & Idan Izhaki – “User Score for Restaurants Recommendation System”
Assignment 2

\[ \hat{r}_{ui} = \mu + b_u + b_i + (q_i + \frac{1}{|M(i)|} \sum_{n \in M(i)} |s_n|)^T p_u \]

set of geographic neighbours
impact of neighbours

Long Jin & Xinchi Gu – “Rating Prediction for Google Local Data”
Assignment 2

Mohit Kothari & Sandy Wiraatmadja – “Reviews and Neighbors Influence on Performance of Business”

Topic model from Google Local business reviews

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<th>“Italian Restaurants”</th>
<th>“Airport &amp; Rentals”</th>
<th>“Computer Repairs”</th>
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Assignent 2

Wikispeedia navigation traces:

Figure 5: Graph of a complete path

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<th>Average Time</th>
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<tr>
<td>Finished Path Back</td>
<td>6.75</td>
<td>158.31</td>
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<tr>
<td>Unfinished Path</td>
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<td>835.29</td>
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<tr>
<td>Unfinished Path Back</td>
<td>5.2</td>
<td>836.00</td>
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Images from Chictopia

Power laws!

Wei-Tang Liao & Jong-Chyi Su – “Image Popularity Prediction on Social Networks”
Crime (Chicago)

Goal: to predict the number of incidents of crime on a given day

Joshua Wheeler, Nathan Moreno, Anjali Kanak
Predicting Taxi Tip-Rates in NYC

(data from archive.org)

(pickup and dropoff)

Distance, time taken, speed, and time of day (also on geo)

Sahil Jain, Alvin See, Anish Shandilya
TAs will do most of the grading, and run office hours (in addition to my own)
Office hours

- I will hold office hours on Tuesday mornings (9:00am-1:00pm, CSE 4102)
- TA office hours will be held on Mondays and Fridays from 10:00am-13:00pm in B275
Most announcements will be posted to Piazza

https://piazza.com/ucsd/fall2017/cse158/home

please participate!